New developments in modeling hogs production and growth at a finer temporal resolution

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Disclaimer

The findings and conclusions in this presentation are those of the author(s) and should not be construed to represent any official USDA of U.S. Government determination or policy.

Presentation outline

1. Swine survey at NASS
2. Swine industry characterization
3. Inventory equations
4. Case study
5. Conclusion

Swine survey at NASS

NASS conducts quarterly surveys to evaluate status of US swine industry

Reported quantities over previous three months:

- Monthly **pig crop**
- Monthly **sows farrowed**

Reported inventories at the first day of the surveyed quarter:

- **Breeding herd**
- **Market hogs** distinct in weight groups:
  1. Less than 50 lbs
  2. 50-119 lbs
  3. 120-179 lbs
  4. More than 180 lbs

Pros and cons of current modeling approaches

Constrained Kalman filter model

- Reliable during periods of equilibrium
- Too rigid during periods of shocks

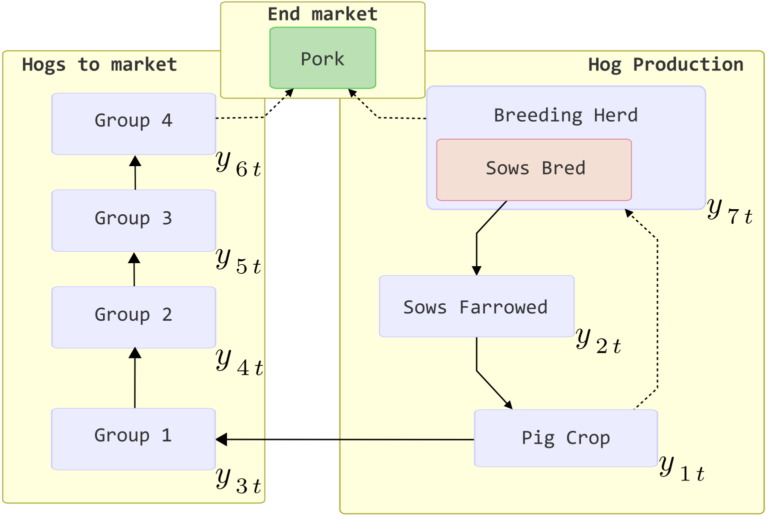
Sequential generalized linear models

- Very flexible
- Ignoring biological constraints

Objectives of the new model

1. Satisfy constraints without forcing them
2. Produce stable estimates during equilibrium periods
3. Flexibile formulation to quickly adapt estimates during shocks
4. Predict national inventories at a finer temporal resolution

Swine population dynamics



Breeding dynamics

$$\begin{cases} z_{1,t} = \rho_t \, z_{2,t} \\ z_{2,t} = \varphi \, y_{7,t-2} + \varepsilon_{2,t} \end{cases}$$

$z_{1,t}$ monthly pig-crop at time t

$z_{2,t}$ monthly sows farrowed at time t

$y_{7,t-2}$ size of breeding herd (inventory) at time $t-2$

ρ_t piglets per sows at time t

φ breeding/farrowing rate

$\varepsilon_{2,t}$ error in modeling sows farrowed

$$y_{7,t} = \varphi^{-1} \left(z_{2,t+2} + \varepsilon_{2,t+2} \right)$$

Time series models

Account for trend, seasonality, and auto-correlations

Dynamics of logarithms of pig crop and sows farrowed are modeled by SARIMA model (Box et al., 2015)

The model choice for $\log(z_{1,t})$ and $\log(z_{2,t})$ is

$$\text{SARIMA}(2, 1, 2) \times (2, 1, 2)_{12}$$

Model fitting via LASSO (Tibshirani, 1996) for automatic selection of a sub-model

Inventory equations

$$
\begin{cases}
y_{3,t} = \zeta_{t-1}\, z_{1,t-1} + \zeta_{t-2}\, z_{1,t-2} + \zeta_{t-3}\, \alpha_1\, z_{1,t-3} + \varepsilon_{3,t}, \\
y_{4,t} = \zeta_{t-3}\, (1-\alpha_1)\, z_{1,t-3} + \zeta_{t-4}\, z_{1,t-4} + \zeta_{t-5}\, \alpha_2\, z_{1,t-5} + \varepsilon_{4,t}, \\
y_{5,t} = \zeta_{t-5}\, (1-\alpha_2)\, z_{1,t-5} + \zeta_{t-6}\, \alpha_3\, z_{1,t-6} + \varepsilon_{5,t}, \\
y_{6,t} = \zeta_{t-6}\, (1-\alpha_3)\, z_{1,t-6} + \zeta_{t-7}\, \alpha_4\, z_{1,t-7} + \varepsilon_{6,t},
\end{cases}
$$

$z_{1,t}$ monthly pig-crop at time t

$y_{2+i,t}$ market hogs , for weight group $i = 1, \ldots, 4$

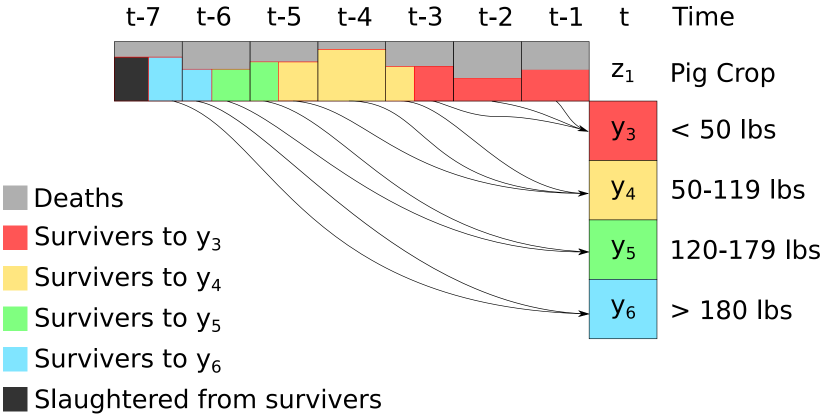
$\varepsilon_{2+i,t}$ errors in modeling market hogs

α_i projection parameters, for $i = 1, \ldots, 4$

ζ_t survival rates at time t

Inventory equations (cartoon interpretation)

Death rates and allocation percentages are not realistic!



Case study

Historical estimates from 2008 are combined with survey data up to 2017

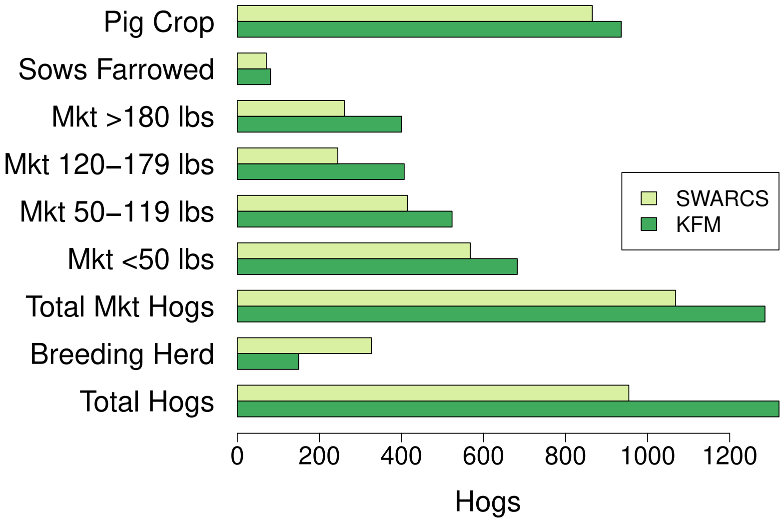
The proposed model (SWARCS) and the Kalman filter (KFM) are both used to estimate inventory numbers between 2013 and 2017

The results from the two models are compared against

- Final estimates[1] (NASS USDA, 2019)
- Root mean squared error (RMSE) as selection criterion

[1] https://downloads.usda.library.cornell.edu/usda-esmis/files/jd472w45t/h128nn160/m613n493n/hgpgsb19.pdf

Model comparisons via RMSE



Conclusion

For the new model

1. Biological dynamics are satisfied without forcing constraints
2. Stable estimates are produced by a flexible formulation of survival rates
3. Estimates can be produced on a monthly basis at US level

Future work

- Improving breeding herd estimates
- Modeling spatial relationships among states

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Thank you!

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